Vol.1, No. 4 May 2023
e-ISSN: 2963-7589
Economic and Business Journal | ECBIS
https://ecbis.net/index.php/go/index

ADOPTION OF SMALL-SCALE IRRIGATION AND ITS IMPACT ON HOUSEHOLD'S INCOME IN DUGDA DISTRICTS, EAST SHEWA ZONE, OROMIA, ETHIOPIA

Gemechu Mulatu

Wollega University / Ethiopia

E-mail: mulatugemechu02@gmail.com

Abstract

The major of this study was to estimate the impact of Adoption of Small-Scale Irrigation in Dugda district. Data were collected from both primary and secondary data sources. Primary data was collected from 384 household heads in four kebeles of the district using structured questionnaire. Descriptive, logit and propensity score matching techniques were used for data analysis. The study finding from the propensity score matching technique revealed that the incomes of adopters of small scale irrigation were increased by 37,696.06ETB per annum. This calls for strengthening the available irrigation facilities and expansion of irrigation sector in the study area.

Keywords : ***Irrigation, Impact, Prospensity Score Matching***

1. INTRODUCTION

Ethiopia is a nation with about 91.7 million people of which 20% are urban and 80% are rural dwellers. The livelihood of rural people is dependent on crop and livestock production. The country has an area of 1.14 million square kilometres (World Bank, 2013). Like most Sub-Saharan African countries, agriculture is the backbone of the country's economy. It contributes about 38.8% to GDP (NBE, 2016), employs 83.4% of the rural population, 80% of export earnings, and provides 75% of the raw material requirement of the country's agro-industries (ILO, 2014). The capability of the country to address poverty, food insecurity and various economic problems is highly dependent on the performance of the agricultural sector (EEA, 2013).

Agriculture has its own economic and social benefits, the production of different crops in the country is mostly on a small scale and average crop yield is very low (Kalkidan *et al*., 2016). For a country like Ethiopia, which is struggling with a burgeoning population while the subsistence rain-fed agriculture is under the mercy of inconsistent rainfall, water resource development is believed to have an imperative role in the agricultural, socio-economic, and industrial development (Abebaw and Mesfin, 2015).

Ethiopia is believed to have the potential of 5.1 million hectares of land that can be developed for irrigation through pump, gravity, pressure, underground water, water harvesting and other mechanisms (MoFED 2010a, b). The total current irrigated land area accounts for approximately 5% of the total cultivated land. When the traditional schemes are not considered, the irrigated land area covers a minimum of approximately 1.6% of the total cultivated area. Ethiopia covers 12 river basins with an annual runoff volume of 122 billion m3 of water and an estimated 2.6 billion m3 of groundwater potential. This amounts to 1707 m3 of water per person per year, which is a relatively large volume. However, due to lack of water storage capacity and large spatial and temporal variations in rainfall, there is not enough water for most farmers to produce more than one crop per year. Given the water available, the promotion of water-related technologies, especially irrigation, at both small and large scales, make sense (Awulachew et al. 2005; Melese and Moges, 2021).

To several researchers, the adoption of small-scale irrigation has had a positive impact on household income. Jules and Seungjee (2021) applied propensity score matching and found that adoption of Small-Scale Irrigation had a positive impact on land productivity. Tsegazeab and Surajit (2016); Alemu and Moges (2021); Kebede et al (2021); Gadisa and Gebrerufael (2021), estimated the impact of participation in small-scale irrigation and found that the average treatment effect on the treated (ATT) result revealed that participation in irrigation has significantly and positively affected household income. Eliyas et al (2021) used endogenous switching regression model and found that the positive and significant impact of irrigation schemes had increased users' total income by 7829 ETB (8.5%), as compared to non-users. Tekle et al (2020) applied Heckman's two-step econometric procedure and the inverse mill ratio result shows that the users are 26% better off than the non-users. Yilma et al (2021) found that adoption of Small-Scale Irrigation had a positive impact on crop production, consumption, and revenue generation which all together indicated improvement in food security.

Thus, to the best of the researcher's knowledge, there is no consensus among scholars and researchers on the impact of irrigation on client's income and most of the research in this area is descriptive with few statistical tests. Additionally, the researcher could not find any study undertaken on the determinant of farm households' participation in irrigation and its impact on their income in the study area. Therefore, this study was designed to identify the factors which affect the adoption of small-scale irrigation on the income of farm households in Dugda woreda by using descriptive statistics and an econometric model through logit and Propensity score matching model.

The general objective of the study was to identify the major determinants of participation of farm households in the irrigations' program and its impact on their income in the case of Dugda District, Oromia, Ethiopia.

Vol.1, No. 4 May 2023
e-ISSN: 2963-7589
Economic and Business Journal | ECBIS
https://ecbis.net/index.php/go/index

2. RESEARCH METHOD

2.1 Types and Sources of Data

Both primary and secondary sources of data were used for the study. The primary data were collected from sample rural household heads using structured questionnaires prepared and pre-tested for its validity and reliability. Data collected were socio-economic, demographic, geographic, institutional characteristics, existing income sources, and factors that affect adoption of small-scale irrigation by smallholder farmers.

Secondary data that include physical characteristics of the area and population size were collected from published and unpublished documents, internet sources, reports and other relevant materials. These types of data were collected from different governmental and non-governmental bodies that are found at district, zonal, regional, and national levels.

2.2 Sampling Technique and Sample Size

To select representative sample households, a multi-stage sampling technique was followed. First, Dugda District was chosen based on the availability of irrigation schemes. In the second stage after discussion with development agents, four kebeles best endowed with irrigation schemes were identified. Accordingly, Bekele Girissa, Shubi Gamo, Walda Kallina, and Walda Maqdalla were chosen.

At the third stage, to choose the correct sample size, the formula recommended by Kothari [2004] was used. This formula is:

$$n = \frac{Z^2 \times P(1-P)}{e^2} = \frac{1.96^2(0.5)(0.5)}{(0.05)^2} = 384$$

Where,

n - Desired sample size

Z - Values of standard variant at 95% confidence interval (Z = 1.96).

P - The estimated proportion of farmers who adopted small-scale irrigation and is unknown and P= 0.5 was used to obtain a maximum number of sample household heads. The sample size determine by the formula was 384 households and samples were taken from each kebeles proportional to the size of the number of household heads in each kebeles.

2.3 Methods of Data Analysis

The empirical data was analyzed using descriptive, inferential statistics and econometric models. In what follows, these tools are outlined and discussed in detail.

2.3.1 Descriptive statistics

The collected raw data will be edited and analyzed using appropriate statistical tools such as mean, percentages, frequencies, and standard deviations to summarize and categorize the information that was collected. Cross tabulation, t-test and chi-square tests were also employed to compare small-scale irrigation users and non-users in terms of different explanatory variables.

2.3.2 Propensity Score Matching

The major objective of this study is to examine the impact of adoption of small-scale irrigation on household income in Dugda Districts. To analyze such type of impact econometric models such as regression discontinuity design, Heckman's two-stage model and semi-parametric methods (difference-in-difference approach, propensity score matching) are widely used.

Propensity score matching (PSM) and double-difference or difference-in-difference (DID) are the common methods for program impact evaluations. Under the difference-in-difference approach, the impact of the project is the difference between the outcomes in the second less the first period (Baker, 2000). Difference-in-difference (DID) methods are advantageous in the sense that they relax the assumption of conditional exogeneity or self-selection on observed characteristics. Moreover, they provide an appealing and intuitive way to account for selection based on unobserved characteristics. This method is not suitable for the current study, as the difference-in-difference approach needs a baseline survey.

The regression discontinuity design (RDD) is an impact evaluation method that can be used for programs that have a continuous eligibility index with a clearly defined cut-off score to determine who is eligible and who is not. Because the regression discontinuity design (RDD) method estimates the impact of the program around the cut-off score, or locally, the estimate cannot necessarily be generalized to units whose scores are further away from the cut-off score, this is, where eligible and ineligible individuals may not be as similar. The fact that the RDD method will not be able to compute an average treatment effect for all program participants can be seen as both a strength and a limitation of the method, depending on the evaluation question of interest.

The Heckman sample selection model is a useful model when there is a selection equation and a continuous outcome variable. It assumes that the functional form of the causal relationship between outcome, treatment, and covariates is linear. Technically, the Heckman model is identified when the same independent variables in the selection equation appear in the outcome equation. However, identification only occurs because of distributional assumptions about the residuals alone and not due to variation in the explanatory variables. Identification is essentially possible due to the non-linearity in the selection equation, which is introduced into the outcome equation through the inverse Mill's ratio. The problem with this model is that it is difficult to get a precise estimate of the outcome equation because of high multicollinearity and large standard errors. This is the case even if you do not include all of the variables from the selection equation in the outcome equation.

The choice of PSM for this study is motivated by the lack of observational data for the control group, thus requiring construction of a statistical comparison group based on a model of the probability of adoption of small-scale irrigation schemes. The propensity score approach can reduce bias in observational studies (Rosenbaum, 1987, 2004; Rosenbaum and Rubin, 1985; Rubin and Thomas, 1992) through the identification of non-participants who are similar to participants in all relevant pre-participation characteristics. Matching helps to find a group of treated individuals (participants) similar to the control group (non-participants) in all relevant pre-treatment characteristics where the only adoption of small-scale irrigation schemes and the other group did not. The detailed specification of PSM is found in Caliendo and Kopeinig (2008). The estimation process is done using psmatch2 in STATA 15.

The impact of the adoption of small-scale irrigation schemes of an individual is the difference between potential outcomes with and without participation:

$$\Delta_i = Y_{1i} - Y_{oi}$$

Where states 1 and 0 correspond, participant, and non-non-participant, respectively. Y is the annual income of the ith household head.

To evaluate the impact of the adoption of small –scale irrigation scheme on a household's income over the population; we may compute the average treatment effect (ATE):

$$ATE = E[\Delta_i] = E(Y_1 - Y_0)$$

Most often, we want to compute the average treatment effect on the treated (ATT):

$$ATT = E[\Delta_i] = E(Y_1 - Y_0 / D = 1)$$

Where D = 1 refers to the treatment.

The problem is that not all of these parameters are observable, as they rely on counterfactual outcomes. For instance, we can rewrite ATT as:

$$ATT = E(Y_1 | D = 1) - E(Y_0 | D = 1)$$

Assumption and Data Requirements of PSM

For the matching method to be valid, two key assumptions should be satisfied. These are Conditional Independence (CIA) and the presence of common support (Khandker et al., 2010).

Conditional independence: There is a set X of covariates, observable to the researcher, such that after controlling for these covariates, the potential outcomes are independent of the treatment status:-

$$(Y_1;Y_0) \perp D|X$$

This is simply the mathematical notation after controlling for X; the treatment assignment is "as good as random". The CIA is crucial for correctly identifying the impact of the program since it ensures that the treated and untreated groups differ and these differences may be accounted to reduce the selection bias. This allows the untreated units to be used to construct a counterfactual for the treatment group.

Common support: For each value of X, there is a positive probability of being both treated and untreated:

$$0 < P(D = 1|X) < 1$$

Even in the case of a randomized experiment, participants selected for treatment may choose not to be treated, or may not comply with all aspects of the treatment regime. In this sense, even a randomized trial may involve bias in evaluating the effects of treatment and non-experimental methods may be required to adjust for that bias. When the assumptions of unconfoundedness and common overlap are satisfied, the treated group is matched to the non-treated group for each value of X using an appropriate matching algorithm.

Propensity score matching involves the following steps:

First, propensity score (PS) is estimated using a probit or logit model. This method linearizes distances from the 0-1 interval. In estimating the logit/probit model, the dependent variable is participation, which takes the value of 1 household head adopter of a small-scale irrigation scheme and 0 otherwise.

The second step is selecting a Matching Algorithm. Once the propensity scores are estimated participant household heads are then matched with non-participants with similar propensity scores. This seeks an appropriate matching estimator. There are a number of matching estimators, which can be employed. The most common matching algorithms used in PSM include:

Nearest neighbor matching: According to Caliendo and Kopening (2008), the most straightforward matching estimator is the Nearest Neighbor. Every treated unit can be matched with one or more control units. If the matching is based on one control unit, it causes to minimize bias and increases variance. Matching can be done with or without replacement. However, without replacement process has an advantage that it results in a low variance. In nearest-neighbor matching, there is a problem of high differences in propensity score of participants and non-participants, which can cause poor results.

Calliper or Radius matching: Nearest neighbor, matching faces the risk of bad matches if the closest neighbor is far away (Caliendo, 2008). To avoid this problem researcher uses the second alternative matching algorithm called calliper matching. In the radius matching approach, an individual from the control group is chosen as a matching partner for a treated individual who lies within the specified radius in terms of the propensity score (Dehejia and Wahba, 2002). The smaller the radius, the better quality is the matching. However, radius matching is usually faced with the risk of bad matches, especially when the closest neighbor is far away.

Kernel matching: For each adopter of small-scale irrigation users, a weighted average of the outcome of all non-cooperative marketing is derived from the propensity score. All treated units are matched with a weighted average of all controls with weights which are inversely proportional to the distance between the propensity scores of treated and controls (Becker and Ichino, 2002; Venetoklis, 2004).

In the third stage, defining the region of common support and balancing tests is conducted (Bryson et al., 2002). According to Caliendo and Kopeinig (2005) and Heinrich et al., (2010) a simple histogram or density-distribution plots of propensity scores for the two groups, along with a comparison of the minimum and maximum propensity score values. In each distribution, it can be used to show the extent to which there is an overlap in the propensity scores of the treatment and comparison units.

In the fourth stage, balancing tests are conducted to check whether the treatment and comparison groups are balanced in their propensity scores and observed variables. Although a treated group and its matched non-treated comparator might have the same propensity scores, they are not necessarily observationally similar if misspecification exists in the participation equation.

Formally, one needs to check if

$$\hat{P}(\textit{observed variables} \mid \textit{Treatment} = 1) = \hat{P}(\textit{observed variables} \mid \textit{Treatment} = 0). \quad (10)$$

In the PSM method, choosing the covariates is important because they directly affect the estimation outcomes. Lee (2005) suggests that the chosen covariate (X) must be predetermined and affect both outcome (Y) and treatment (D). In addition, to avoid the causality bias, D should not affect X.

After propensity scores have been estimated and a matching algorithm has been chosen, the ATT is used to measure the impact of the adoption of small-scale irrigation schemes on household income is evaluated. ATT is the difference in the mean value of the outcome variable between a 'with and without' intervention that measures the impact of an intervention.

Finally, to ensure that the CIA is not undermined by potential unobserved covariates that might have significant influences on the selection of treatment and treatment outcomes, a simulation-based sensitivity analysis is conducted based on Rosenbaum's bounding approach (Rosenbaum, 2002).

3. RESULTS AND DISCUSSION

This sub-section presents descriptive statistics of the demographic, socioeconomic, and institutional characteristics of the sample households. There is ample literature that shows the relation between the socio–demographic as the covariates of the adoption of small-scale irrigation schemes. Among the different socio–demographic factors that have a relation to the adoption of small-scale irrigation schemes, some of them are discussed as follows.

3.1 descriptive Results

Income: In this research, annual income was considered as the outcome variable. The incomes of both irrigation users and non-users were compared. The mean household income for the study area is 26,807.95ETB with a standard deviation of 21,843.75ETB per annum. The mean household income for non–users was 18,278.19ETB and for small-sale irrigation users it was 42,905.47 etb. The t- value is -12.45 and is statistically significant at a 1% significance level. This indicates that there is a statistically significant mean difference between users and non-users in terms of their incomes.

The educational level of the household head: Education is helpful to open the minds of farmers to new knowledge and innovations. The mean educational attainment of the overall sample household was 4.83 grades with a standard deviation of 3.26. The mean for non–irrigated users was 4.585 grades and the mean for irrigation users was 5.3 grades. The t value (t = -2.05) indicates that there is a statistically significant mean difference between irrigation users and non-users at less than 5 % significance level.

Distance to market: The mean distance of all-sampled household homes from the nearby markets is 5.49km with a standard deviation of 3.07Kms. The mean for non-users was 5.123 km and the mean for users was 6.204 km. The t value (t = -3.3) was statistically significant at less than a 1% significance level. There shows that there is a significant mean difference between irrigation users and non-users in terms of distance from the nearby markets.

Family size: For the overall sample, the average family size for the study area was 5.04 with a standard deviation of 2.29. The mean family size for non –irrigation users was 5.275 while for users it is 4.594. The t value (t = 2.8) shows that there is a significant mean difference between the two groups.

Table 1: Two-sample t-test with equal variances

Variables	Overall sample(n = 384)		Mean for Non – users (n1=251)	Mean for Users (n2=133)	Difference	St Err	T value
	Mean	Standard Deviation					
The income per cropping season in ETB	26,807.95	21,843.75	18,278.19	42,905.47	-24627.27	1978.70	-12.45***
Age of household head in years	39.62	13.81	39.398	40.03	-0.632	1.483	-0.45
The educational level of the household head	4.83	3.26	4.585	5.301	-0.715	0.348	-2.05**
Distance to market in km	5.49	3.07	5.123	6.204	-1.081	0.326	-3.3***
Family size in numbers	5.04	2.29	5.275	4.594	0.681	0.244	2.8***

Source: Computed from survey data (2022)

Table 2: Descriptive statistics of dummy variables

Variables	Category	Irrigation			Chi-squared
		Non- user	user	Total	
Sex household head	Female	35(60.34%)	23(39.66%)	58 (100%)	0.76
	Male	216(66.26%)	110(33.74%)	326 (100%)	
Access to credit	No	130(92.20%)	11(7.80%)	141 (100%)	185***
	Yes	121(49.79%)	122(50.21%)	243 (100%)	
Access to information	No	126(92.65%)	10(7.35%)	136 (100%)	69.23***
	Yes	125(50.40%)	123(49.60%)	248 (100%)	

Source: Computed from survey data (2022)

Access to credit: as indicated in Table 2, from the total farmers who have access to credit 121(49.79%) were non-irrigation users while the remaining 122(50.21%) are credit users. The chi-square result is 185 and it is statistically significant at less than 1% significance level. This shows that there is a significant association between access to credit and the adoption of small-scale irrigation schemes.

Access to information: from the total farmers who have access to information 125 (50.40%) were non-irrigation users and the remaining 123(49.60%) are irrigation users. The chi-square result is 69.23 and it shows that there is a statistically significant association between access to information and adoption of small-scale irrigation.

3.2 Results of Propensity Score Matcning Techniques

Step I: the first step of using propensity score matching is to select the covariates to be used in the model. Ideally, propensity scores are created from covariates related adoption of small-scale irrigation and the outcome variable -income. Accordingly, sex of the household head, age of the household head, educational attainment of the household head, distance to nearby market, and access to credit, number of extension visits, family size, and access to information were included in the estimation of propensity score.

Step 2: To estimate propensity score or probability adoption of small-scale irrigation schemes, both logistic regression model and probit regression model can be used. Akaike's and Schwarz's Bayesian information criteria was used to compare the two models. The "smaller the AIC and BIC": given two models, the better fitting the model. Accordingly, the propensity score matching was estimated using a logistic regression model.

ECONOMICS AND BUSINESS JOURNAL
Vol.1, No. 4 May 2023
e-ISSN: 2963-7589
Economic and Business Journal | ECBIS
https://ecbis.net/index.php/go/index

Table 3 : Econometric model result

Independent variables	Probit regression model result			Logistic regression model result		
	Coefficient	St.Err.	dy/dx	Coefficient	St.Err.	dy/dx
Sex of household head	-0.245	0.189	-0.087	-0.531	0.334	-0.112
Age of household head	0.002	0.005	0.001	0.004	0.009	0.001
Educational attainment	0.077	0.024	0.026***	0.125	0.042	0.024***
Distance to a nearby market	0.077	0.028	0.026***	0.138	0.048	0.027***
Access to Credit	0.567	0.27	0.183**	0.985	0.445	0.18**
Number of Extension visits	0.48	0.311	0.157	0.88	0.574	0.162
Family size	-0.056	0.034	-0.019***	-0.08	0.06	-0.016***
Access to Information	0.952	0.279	0.292***	1.682	0.595	0.288***
Constant	-2.208	0.445		-3.965	0.808	
Pseudo r-squared		0.267		Pseudo r-squared		0.271
Chi-square		98.435***		Chi-square		82.45***
Akaike criteria (AIC)		381.06		Akaike criteria (AIC)		379.147
Bayesian crit. (BIC)		416.615		Bayesian crit. (BIC)		414.703
*** p<.01, ** p<.05, * p<.1						
(*) dy/dx is for discrete change of dummy variable from 0 to 1						

Source: Computed from survey data (2022)

The overall significance and fitness of the model can be checked with the Chi-square = 82.45 value; accordingly, Prob > chi2 = 0.000 indicates that the independent variables reliably predict the dependent variable. The study finding has revealed that Educational attainment, distance to a nearby market, access to credit, family size and access to information are the main variables that are statistically significant factors determining a household's adoption of small-scale irrigation schemes.

Education: Having more years of schooling is very much important for smallholder farmers to use new tools and technologies to enhance operations and increase their profit. This variable has a positive marginal effect and is statistically significant at a 1% significance level. The marginal effect of this variable indicates that a one-year increase in years of schooling by household heads increases the probability of adoption of small-scale irrigation schemes by 2.4%. The probable justification is that education enables farm households to engage in small-scale irrigation due to the benefit they derive from participation in irrigation. This result corroborates the findings of Tsegazeab and Surajit (2016) and Tekle et al (2020).

Distance to nearby market: the positive marginal effect = 0.027 indicates that the farther away residence of the farmer from the market the more adopter of irrigation practices. The probable justification might be due to the fact most irrigation scheme users reside nearer to irrigation water sources and far away from nearby markets.

Access to credit: Getting credit solves the problem of cash shortages during the cropping season. Having funds to finance farm activities would enhance the adoption of small-scale irrigation by smallholder farmers. The marginal effect (mfx = 0.18) showed that access to irrigation increases the probability of adoption of small-scale irrigation schemes by 18%. This result is consistent with the findings of Tekle et al (2020).

Family size: this variable has a negative marginal effect. This indicates that an increase in family size by one member reduces the probability of adoption of irrigation schemes by 1.6% and is statistically significant at a 1% significance level.

Information: Having information is important for making decisions for the adoption of agricultural practices. The marginal effect of this variable is 0.288 and statistically significant at a 1% significance level. This indicated that access to information increases the probability of adoption of small-scale irrigation by 28.8%. This keeps the findings of Tekle et al (2020).

Table 4: Descriptive Statistics of propensity score

Pscore	Observation	Mean	Std. Dev.	Minimum	Maximum
Non-irrigation users	251	0.241	0.214	0.004	0.784
Irrigation Users	133	0.556	0.223	0.017	0.889
Overall sample	384	0.35	0.264	0.004	0.889

Source: Computed from survey data (2022)

Table 5: Treatment assignment

Treatment assignment	Off support	On support	Total
Untreated	15	236	251
Treated	20	113	133
Total	35	349	384

Source: Computed from survey data (2022)

The region of common support needs to be defined where distributions of the propensity score for treatment and comparison group overlap. Some of the participant and nonparticipant observations falling outside the region of common support may have to be dropped. If there is insufficient overlap, then this suggests that there are some treated observations that are not comparable to any control observations, or vice-versa. In our study a common support region was imposed on both sides, i.e. by dropping treatment observations whose estimated propensity scores are higher than the maximum or lower than the minimum propensity score of the controls and vice versa (i.e. dropping control observations whose estimated propensity score is higher than maximum or lower than minimum propensity score of the treated). Therefore, the common support region is between 0.017 and 0.784 and 35 household heads were discarded from the impact analysis. T

Vol.1, No. 4 May 2023
e-ISSN: 2963-7589
Economic and Business Journal | ECBIS
https://ecbis.net/index.php/go/index

able 6: Performance of the different matching algorithms

Matching Estimator		Matching performance criteria			
		Balancing test*	Pseudo-R^2	Mean bias	Matched sample size
Nearest neighbor	neighbor(1)	8	0.026	9.4	349
	neighbor(2)	7	0.01	5.2	349
	neighbor(3)	7	0.011	6.4	349
Kernel	bwidth (0.01)	8	0.012	5.9	308
	bwidth (0.05)	8	0.009	6.5	349
	bwidth (0.1)	8	0.007	6.8	349
Calliper or Radius	Radius calliper (0.01)	8	0.011	5.6	309
	Radius calliper (0.05)	8	0.008	5.6	349
	Radius calliper (0.1)	8	0.007	7.1	349

* Number of independent variables with no statistically significant mean difference between the matched groups of households.

Source: Computed from survey data (2022)

Following that one has to decide which matching algorithm to choose and determine the region of common support. Subsequently, the matching quality has to be assessed and treatment effects and their standard errors have to be estimated. This seeks an appropriate matching estimator. There are several matching estimators, which can be employed. The best way to select the matching estimator is to select the matching algorithm with the highest balancing test, lower pseudo R2 and highest matched samples. Accordingly, this impact analysis was done using a Kernel with bwidth (0.1).

Table 7: Balancing test

Variable	Mean			t-test		V(T)/ V(C)
	Treated	Control	%bias	t	p>t	
Sex of hh	0.87611	0.8863	-2.8	-0.24	0.814	.
Age of hh	39.929	39.32	4.4	0.32	0.751	0.89
Education	4.7257	5.0978	-11.6	-0.89	0.372	0.72
Distance to a nearby market	5.5762	5.3972	5.8	0.46	0.646	1.19
Credit	0.90265	0.87884	5.9	0.57	0.568	.
Extension visit	0.90265	0.8781	6.1	0.59	0.557	.
Family	4.6903	4.4629	10.4	0.81	0.418	0.73
Information	0.9115	0.88267	7.2	0.71	0.478	.

Source: Computed from survey data (2022)

Then, the covariates after matching must be insignificant. The use of standard difference can be used to compare the balance in measured variables between treated and untreated subjects in the matched sample with that in the unmatched sample. Furthermore, it allows for the comparison of the relative balance of variables measured in different units. Therefore, it is possible to proceed to evaluate the impact of the adoption of small-scale irrigation on the outcome variable income. The substantial overlap in covariates between the exposed and unexposed groups must exist for us to make causal inferences from our data.

Table 8: Outcome evaluation

Sample	Controls (no-adopters)	Treated (adopters)	Difference	S.E.	T-stat
Unmatched	42,905.47	18,278.19	24,627.28	1978.7	12.45***
ATT	45,326.52	19,008.93	26,317.59	2859.725	9.2***
ATU	18,571.04	61,715.26	43,144.22	.	.
ATE			37,696.06		

Source: Computed from survey data (2022)

The Average Treatment effect on the Treated (ATT) revealed an increment that comes on the adopters of small-scale irrigation schemes. This indicates that the adoption of small-scale irrigation schemes has brought a significant impact on the adopter household's annual income. The t-stat value is statistically significant at a 1 % significance level. On average, the result reveals that the incomes of adopters increased by 37,696.06ETB per annum. The probable justification is that in the study area irrigation users mainly produce cash crops and

ECONOMICS AND BUSINESS JOURNAL

Vol.1, No. 4 May 2023
e-ISSN: 2963-7589
Economic and Business Journal | ECBIS
https://ecbis.net/index.php/go/index

earn more income than non-irrigation users. This result keeps the findings of Kebede et al (2021); Gadisa and Gebrerufael (2021).

Table 9: Rosenbaum bounds for participation in irrigation (N = 384 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	0	**0**	0.5	0.5	0.5	0.5
1.5	0	0	-3.30E-07	0.5	-3.30E-07	0.5
2	2.20E-16	0	-3.30E-07	0.5	-3.30E-07	0.5
2.5	1.50E-13	0	-3.30E-07	0.5	-3.30E-07	0.5
3	1.40E-11	0	-3.30E-07	0.5	-3.30E-07	0.5
3.5	3.50E-10	0	-3.30E-07	0.5	-3.30E-07	0.5
4	4.10E-09	0	-3.30E-07	0.5	-3.30E-07	0.5
4.5	2.70E-08	0	-3.30E-07	0.5	-3.30E-07	0.5
5	1.30E-07	0	-3.30E-07	0.5	-3.30E-07	0.5
5.5	4.40E-07	0	-3.30E-07	0.5	-3.30E-07	1
6	1.20E-06	0	-3.30E-07	0.5	-3.30E-07	1
6.5	3.00E-06	0	-3.30E-07	0.5	-3.30E-07	1
7	6.50E-06	0	-3.30E-07	0.5	-3.30E-07	1
7.5	0.000013	0	-3.30E-07	1	-3.30E-07	1
8	0.000023	0	-3.30E-07	1	-3.30E-07	1
8.5	0.000038	0	-3.30E-07	1	-3.30E-07	1
9	0.00006	0	-3.30E-07	1	-3.30E-07	1
9.5	0.000091	0	-3.30E-07	1	-3.30E-07	1
10	0.000133	0	-3.30E-07	1	-3.30E-07	1

* gamma-log odds of differential assignment due to unobserved factors
sig+ - upper bound significance level
sig- - lower bound significance level
t-hat+ - upper bound Hodges-Lehmann point estimate
t-hat- - lower bound Hodges-Lehmann point estimate
CI+ - upper bound confidence interval (a= .95)
CI- - lower bound confidence interval (a= .95)

Source: Computed from survey data (2022)

Sensitivity analysis is the last step of carrying out propensity score matching analysis. Based on CIA, the treatment effect could be estimated with matching estimators on selected observable characteristics. However, unobserved variables that affect assignment to the treatment and the outcome variable simultaneously might result in hidden bias called unobserved heterogeneity (Caliendo & Kopeinig 2005). Since it was not possible to estimate the magnitude of selection bias with non-experimental data, this problem was addressed using "Rbounds" bounding approach proposed by Rosenbaum (2002). From the above, it seems that the result is insensitive to unobserved bias up to gamma greater than 10.

Therefore, household improvement indicated result is the result of adoption of small-scale irrigation.

4. CONCLUSION

Household income is an important economic indicator because it determines the state of household welfare. The main objective of this study was to estimate the impacts of the adoption of small-scale irrigation on household income in Dugda district. Four kebeles with potential (Bekele Girisa, Shubi Gemo Walda- kellina and Welda Mek della kebeles) were selected. A simple random sampling technique was followed to select 384 households from both irrigation users and non-non-users. Of the total sample respondents, 251 of them were non-users and 133 of them were irrigation users. The propensity score-matching technique was used for data analysis and the result of the study concludes that adoption of small-scale irrigation improves household income. Therefore, government and non-governmental organizations should expand and strengthen irrigation in the study area.

REFERENCES

Abebaw, A., and Mesfin, T. (2015). Challenges and Opportunities of Small-Scale Irrigation Utilization in Rift Valley Basin Ethiopia College of Agriculture. Humbo Woreda, Ethiopia.

Kalkidan, F., Yemiru, T., and Ephrem, T. (2016). Gender involvement in small-scale irrigation agriculture among smallholder farmers in Lume district in the central rift valley, Ethiopia.

Awulachew B, Merrey D, Kamara B, Van Koppen B, De Vries P, Boelee E, Makombe G (2005) Experiences and opportunities for promoting small-scale/micro irrigation and rainwater harvesting for food security in Ethiopia. International Water Management Institute, Addis Ababa

MOFED (2010a) The Federal Democratic Republic of Ethiopia, growth, and transformation plan (GTP) 2010/11–2014/15, Draft. 2010, Addis Ababa, Ethiopia

MOFED (2010b) Trends and prospects for meeting MDGs by 2015, millennium development goal report, Addis Ababa, Ethiopia

World Bank. 2023. World Development Indicators Database, WDI.Xls.

EEA (Ethiopian Economics Association). 2013. Report on the Ethiopian Economy with Particular Reference to the Manufacturing Sector Addis Ababa, Ethiopia.

ILO (International Labour Organization). 2014. Decent Work Country Programme 2014-15, ETHIOPIA, Addis Ababa, Ethiopia.

Kothari, C. 2004. Research Methodology: Methods and Techniques, 2nd Edition, Wisha, Prakasha, New Delhi.

National Bank of Ethiopia. (NBE) (20013/14) Annual Report, Addis Ababa, Ethiopia

Tekle Leza, Temesgen Fanta, and M. Senapathy (2020) Effect of Small Scale Irrigation on Improving Household Income: The Case of Hembecho Irrigation Scheme in Boloso Sore Woreda, Wolaita Zone, Ethiopia, IOSR Journal of Economics and Finance (IOSR-JEF) e-ISSN: 2321-5933, p-ISSN: 2321-5925.Volume 11, Issue 3 Ser. VIII (May – June 2020), PP 17-27, www.iosrjournals.org

Kebede, T., S.A. Shah, M. A. Khan, and M. Asif. (2021). Impact of Small Scale Irrigation Project on Households Income: An Empirical Study in Southwest Ethiopia. AMA.

Rosenbaum, Paul and Rubin, Donald. (1983) Role of the Propensity Score in Observational Studies for Causal Effects.” Biometrika, April 1983, 70(1), pp. 41–55. (Or any of a number by these authors on observational studies

Carolyn J. Heinrich, A. Maffioli, Gonzalo Vázquez (2010) A Primer for Applying Propensity-Score Matching Impact-Evaluation Guidelines, Technical Notes, No. IDB-TN-161, August 2010

Gadisa Muleta and Gebrerufael Girmay (2021), Impact of Small-Scale Irrigation on Household Income in Central Ethiopia: Empirical Evidences from Walmara District, Biometrical Journal 10(2):101-106

Tsegazeab Gebremariam Yihdego and Surajit Ghosal (2016) The Impact of Small Scale Irrigation on Household Income in Bambasi Woreda, Benishangul-Gumuz Region, Ethiopia, International Journal of Scientific and Research Publications, Volume 6, Issue 6, June 2016, ISSN 2250-3153

Melese Alemu and Moges Dessale (2021) Impacts of small-scale irrigation on rural households' income in north eastern Ethiopia, Sustainable Water Resources Management (2022) 8:15, https://doi.org/10.1007/s40899-021-00600-1

Yilma Jambo, Abera Alemu & Workalemahu Tasew (2021) Impact of small-scale irrigation on household food security: evidence from Ethiopia

Yilma Jambo, Abera Alemu and Workalemahu (2021) Tasew (2020) Impact of small-scale irrigation on household food security: evidence from Ethiopia, Agric & Food Secur (2021) 10:21, https://doi.org/10.1186/s40066-021-00294-w